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Sensitivity Analysis of a Photovoltaic Cell with a Single-Diode Model at Maximum Power Point: A Derivative-Based Approach

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ABSTRACT

The necessity of sensitivity analysis has rapidly increased for systems with unknown or uncertain mathematical relationships between inputs and outputs. In this regard, the single-diode model (SDM) of a photovoltaic (PV) cell can be considered an uncertain, complex, nonlinear system with a non-convex relationship between its output power and five unknown electrical parameters as inputs. In this paper, a rigorous mathematical analysis is applied to determine both the local and global sensitivities of the PV cell's output power with respect to the five input electrical parameters at the maximum power point (MPP). The local and global sensitivity analyses are obtained through partial derivatives of the PV power with respect to all five inputs. For the global analysis, all electrical parameters are normalized between 0 and 1 within their feasible ranges of variation. Then, the complex partial derivative functions with normalized variables are approximated using multivariable quadratic functions via the least-squares optimization method. Finally, five separate quintuple integrals of the approximated squared partial derivative functions are numerically calculated in the unit hypercube H^5. Precise quantitative values are reported for both local and global analyses at the MPP. It is verified that the diode ideality factor and the parallel resistance have the highest and lowest impact on SDM performance, respectively.

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1. INTRODUCTION

Nowadays, renewable energy sources have attracted increasing attention due to the critical challenges associated with fossil fuels, such as environmental pollution, energy crises, and climate change (Arandian et al., 2022). The importance of renewable energy sources has further grown with the emergence of smart local energy systems, which can reduce the load and optimize power transmission networks (Deb et al., 2023). Among all renewable energy sources, the utilization of solar energy has increased because of its wide accessibility and considerable efficiency (Ridha et al., 2022). Among various solar energy systems, photovoltaic (PV) technology is the most popular due to its broad range of applications (Diab et al., 2020a).

The solar PV cell is an essential component of a PV system and can be represented by electrical circuits that include one or more diodes. Among them, the single-diode model (SDM), double-diode model (DDM), and three-diode model (TDM) are primarily used for mathematical modeling (Ndi et al., 2021). The SDM, which contains five unknown parameters, is the most common circuit topology owing to its lower complexity and acceptable performance across most PV technologies. However, parameter estimation in the SDM remains a challenging task due to the implicit and nonlinear nature of the current–voltage (I–V) characteristic and the non-uniqueness of candidate solutions (Toledo et al., 2024).

Various methods have been developed for parameter estimation of equivalent circuits with diode(s). These methods can be categorized as analytical (Khezzar et al., 2014; Chouder et al., 2012; Bai et al., 2014), numerical (Bharadwaj et al., 2016; Xu et al., 2017; Xu, 2022), metaheuristic (Mathew et al., 2018; Oliva et al., 2019; Hao et al., 2020; Diab et al., 2020b; Shaheen et al., 2021; Li et al., 2021; Abdelminaam et al., 2021), and hybrid (Et-Torabi et al., 2017; Moshksar and Ghanbari, 2017; Meng et al., 2020; Khalid et al., 2021; Calasan et al., 2021; Ridha et al., 2022; Tifidat et al., 2022) algorithms. Each method has its own advantages and drawbacks in terms of accuracy, complexity, computational burden, and convergence time. All the above approaches aim to estimate the unknown parameters such that the best fit between the measured I–V points and the simulated model can be achieved.

These studies reveal the importance of parameter estimation and PV model identification. Hence, acquiring a general overview of the weight and impact of each parameter in the SDM characteristics can be utilized to improve the PV circuit model's performance. Moreover, PV systems are subject to various faulty conditions, such as partial shading, non-identical mounting angles, dust accumulation, and cell degradation (Nazer et al., 2024). Therefore, identifying the most influential parameters to determine a reliable degradation index for fault detection and PV monitoring is highly important (Bastidas-Rodriguez et al., 2017a).

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Sensitivity analysis (SA) is an effective method for determining the relationships and relative importance of design parameters in physical systems. Thus, identifying the most critical system parameters through SA is an efficient approach to achieve the most optimal design (Malik et al., 2019). In general, SA is a type of uncertainty analysis that measures the effect of a given input on the output (Subhadarsini et al., 2022). Different SA approaches exist, each with specific advantages and limitations. Some SA methods are model-free, while others can only be applied to particular mathematical models (Borgonovo and Plischke, 2016). The classical derivative-based SA approach is a promising method, obtained by directly differentiating the outputs with respect to the input parameters (Jumabekova et al., 2021). It should be noted that derivative-based analysis only provides local information on system parameters at a specific operating point. However, an interesting partial derivative-based approach was developed by Sobol and Kucherenko (2009), which provides a global sensitivity measure. It has been shown that the index derived from this approach is proportional to the global total sensitivity indices. Moreover, this global method has a lower computational burden compared to other global analysis approaches.

Although many studies have been conducted on parameter estimation in the SDM, a comprehensive investigation into the impact of each parameter on model performance has not yet been addressed. In ElShatter and Elhagry (1999), PV characteristics were predicted online using a fuzzy regression model to determine the unknown parameters in the SDM, and a sensitivity analysis of the parameters with respect to the suggested fuzzy input and output data was then introduced. In Zhu et al. (2011), some nonlinear equations were derived for series and parallel resistances, where SA was applied to determine the most stable ones. In Ahmed et al. (2016), a numerical method was used to analyze the sensitivity of certain SDM parameters under various solar radiation and PV temperature conditions. In Bastidas-Rodriguez et al. (2017b), the error effect of each parameter in reproducing the PV module characteristics was presented only schematically. In Khodapanah et al. (2023), a local SA was conducted for a PV system based on the SDM. However, the computed partial derivatives were inaccurate and contained incomplete mathematical expressions. Nevertheless, none of these studies considered global SA for the SDM or presented quantitative values to comprehensively demonstrate the importance of the circuit model parameters.

In this study, an in-depth sensitivity analysis (SA) is conducted for a solar cell with the SDM based on the partial derivative approach. The power of the PV cell is considered as the output because it contains information about both current and voltage variables. The derivation of the partial derivatives of output power with respect to the five unknown inputs is mathematically impractical due to the implicit nature of the I–V characteristic. To address this problem, the explicit mathematical expressions for voltage and current from Jain and Kapoor (2004) are employed. These explicit equations were obtained using the Lambert W-function. Based on these explicit equations, the mathematical expressions for the partial derivatives are derived analytically. Since these equations are complex and highly nonlinear, their qualitative investigation is very difficult and almost impossible. Hence, without loss of generality, the SDM of the R.T.C. France solar cell with the estimated parameters reported in Diab et al. (2020b) is considered as the nominal (baseline) model. It is also assumed that the PV cell operates under the maximum power point (MPP) condition due to the exceptional importance of this operating state. The local sensitivities of all parameters and the corresponding absolute power variations for a 10% deviation from nominal values are investigated. Moreover, the global SA technique proposed by Sobol and Kucherenko (2009) is applied to the R.T.C. France solar cell with the SDM at the MPP. For this purpose, all five unknown parameters are normalized between 0 and 1 using the min–max technique within their admissible ranges of variation. Since the partial derivatives are remarkably complex, they are approximated using multivariable quadratic functions via the least-squares optimization method. Finally, five separate functionals are defined as quintuple integrals of the squared approximated functions with normalized variables. These functionals represent indices for the global SA of the PV cell with the SDM. All five integrals are calculated numerically with low computational burden and high accuracy. It should be noted that all simulations and numerical calculations are implemented in the MATLAB environment. Quantitative values are obtained and discussed for both local and global sensitivity analyses of the PV cell at the MPP. The new insights and main contributions of this work can be summarized as follows:

- A comprehensive analytical and rigorous mathematical analysis is provided to determine the weight of each of the five unknown parameters in the SDM at the MPP. Previous works have presented only partial results and relied mainly on schematic interpretations.
- Both local and global analyses are established, and quantitative values are reported to enable more precise conclusions on SA. To the best of the author's knowledge, this is the first study in this regard.
- Although the algorithms are implemented for the R.T.C. France solar cell, the established results can be generalized to other PV cells with acceptable SDM.
- The results of this study can be utilized in future research for more accurate PV modeling, monitoring, and the development of more reliable fault detection algorithms.

The rest of this paper is organized as follows: the I–V characteristic of a PV cell and its extension to a PV module and PV array are introduced in Section 2. The local and global derivative-based sensitivity analyses for a PV cell with the SDM are discussed in detail in Section 3. Finally, the main results are summarized in Section 4.

2. SINGLE-DIODE MODEL OF A PV CELL/MODULE/ARRAY

The nonlinear $I - V$ characteristic of a PV cell with SDM is given by:

$$\mathrm{I} = \mathrm{F(V, I)} = \mathrm{I_{ph}} - \mathrm{I_0}\left[\exp\left(\frac{\mathrm{V+IR_s}}{\mathrm{aV_t}}\right) - 1\right] - \frac{\mathrm{V+IR_s}}{\mathrm{R_p}} \quad (1)$$

where I and V are the output current and voltage, respectively. The five key unknown parameters include photocurrent (I_{ph}), diode saturation current (I_0), diode ideality factor (a), series resistance (R_s), and parallel resistance (R_p). The known constant thermal voltage (V_t) of the diode is defined as:

$$\mathrm{V_t} = \frac{\mathrm{KT}}{\mathrm{q}} \quad (2)$$

where K is Boltzmann's constant (1.3806503× 10^{-23} J/K), q is electron charge (1.60217646× 10^{-19} C), and T is cell temperature in Kelvin.

For a PV module comprising N_s number of series cells, the $I-V$ equation (1) can be extended as (Tian et al., 2012):

$$I_M = I_{ph} - I_0\left[\exp\left(\frac{V_M+I_M\bar{R}_s}{aN_sV_t}\right)-1\right]-\frac{V_M+I_M\bar{R}_s}{\bar{R}_p} \quad (3)$$

where I_M and V_M are the current and voltage of the PV module. The series resistance and the parallel resistance are updated as (Tian et al., 2012):

$$\begin{cases}\bar{R}_s = N_sR_s\\ \bar{R}_p = N_sR_p\end{cases} \quad (4)$$

For a PV array with N_p number of parallel modules, the $I-V$ characteristic becomes (Tian et al., 2012):

$$I_A = \tilde{I}_{ph} - \tilde{I}_0\left[\exp\left(\frac{V_A+I_A\tilde{R}_s}{aN_sV_t}\right)-1\right]-\frac{V_A+I_A\tilde{R}_s}{\tilde{R}_p} \quad (5)$$

where I_A and V_A are the current and voltage of the PV array. Comparison of (1), (3), and (5) reveals that the diode ideality factor is independent of the PV system size and remains unchanged. The other four parameters are updated as follows (Tian et al., 2012):

$$\begin{cases}\tilde{I}_{ph} = N_pI_{ph}\\ \tilde{I}_0 = N_pI_0\\ \tilde{R}_s = \frac{N_s}{N_p}R_s\\ \tilde{R}_p = \frac{N_s}{N_p}R_p\end{cases} \quad (6)$$

A schematic diagram showing how solar cells are constructed to form a PV module and how modules are arranged to form a PV array is illustrated in Figure 1.

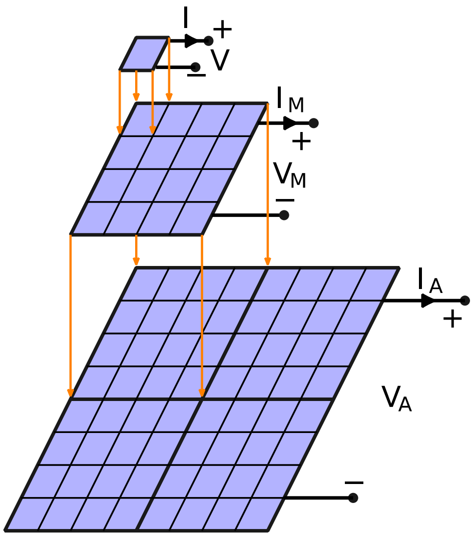

Figure 1. Generation of PV modules and arrays from series/parallel connection of solar cells.

3. DERIVATIVE-BASED ANALYSIS

In addition to estimating the five unknown parameters of the SDM, it is crucial to assess the impact of each parameter on the PV system's performance. Specifically, understanding how each parameter influences the formation of the I–V curve allows us to rank their significance and identify the dominant parameters. This knowledge not only improves parameter estimation techniques but also contributes to the development of robust model-based algorithms for fault detection and system monitoring.

As evident from Equation (1), the voltage and current of a PV cell are nonlinearly interdependent. Therefore, it is more insightful to analyze the electrical power of the PV cell ($P = V \times I$) as the output. In power systems, the goal is to meet load demands at minimal cost, making it essential to quantify and manage the uncertainty in PV power generation (Wen et al., 2021).

Using the chain rule, the effect of uncertainty in a representative parameter such as I_{ph} on the output power can be expressed as:

$$\Delta P = \frac{\partial P}{\partial I_{ph}}\Delta I_{ph} = \left(I\frac{\partial V}{\partial I_{ph}} + V\frac{\partial I}{\partial I_{ph}}\right)\Delta I_{ph}. \quad (7)$$

where ΔP and ΔI_{ph} represent variations in power and photocurrent, respectively. In addition, $\frac{\partial P}{\partial I_{ph}}$, $\frac{\partial V}{\partial I_{ph}}$, and $\frac{\partial I}{\partial I_{ph}}$ are PV power, voltage, and current differentiation with respect to the photocurrent variable. Since $I-V$ characteristic (1) has transcendental inherent ($I = F(V, I)$), determinations of $\frac{\partial V}{\partial I_{ph}}$ and $\frac{\partial I}{\partial I_{ph}}$ are impractical in this current format.

Remark 1: In the referenced studies (Bastidas-Rodriguez et al., 2017b) and (Khodapanah et al., 2023), $\frac{\partial I}{\partial I_{ph}} = 1$ and $\frac{\partial I}{\partial I_{ph}} = N_p$ are reported for a PV cell (module) and a PV array, respectively. However, these mathematical relations are not accurate representations of $\frac{\partial I}{\partial I_{ph}}$ and only contain partial analytical computations, because the calculation of $\frac{\partial I}{\partial I_{ph}}$ for $I = F(V, I)$ in (1) must be repeated infinitely.

In order to obtain the partial derivatives of voltage and current with respect to the five unknown parameters, the explicit mathematical relations presented in Jain and Kapoor (2004) are considered as follow:

$$I = f_1(V) = \frac{R_p(I_0+I_{ph})-V}{R_s+R_p} - \frac{W(g_1(V))aV_t}{R_s} \quad (8)$$

$$V = f_2(I) = -R_sI + (I_{ph} + I_0 - I)R_p - W(g_2(I))aV_t \quad (9)$$

where $W(\cdot)$ is a well-known Lambert W-function and the nonlinear functions $g_1(V)$ and $g_2(I)$ are defined as:

$$\begin{cases}g_1(V) = \frac{R_sI_0R_p\exp(h_1(V))}{aV_t(R_s+R_p)}\\ h_1(V) = \frac{R_p(R_sI_{ph}+R_sI_0+V)}{aV_t(R_s+R_p)}\end{cases} \quad (10)$$

and

$$\begin{cases}g_2(I) = \frac{I_0R_p\exp(h_2(I))}{aV_t}\\ h_2(I) = \frac{R_p(I_{ph}+I_0-I)}{aV_t}\end{cases} \quad (11)$$

In (8) and (9) , V and I are considered as independent variables, respectively. Thus, (7) can be written as:

$$\Delta P = \frac{\partial P}{\partial I_{ph}}\Delta I_{ph} = \left(I\frac{\partial f_2}{\partial I_{ph}} + V\frac{\partial f_1}{\partial I_{ph}}\right)\Delta I_{ph}. \quad (12)$$

Now, $\frac{\partial f_1}{\partial I_{ph}}$ is given by:

$$\frac{\partial f_1}{\partial I_{ph}} = \frac{R_p}{R_s+R_p} - \frac{aV_t}{R_s} \times \frac{\partial W}{\partial g_1} \times \frac{\partial g_1}{\partial I_{ph}} \quad (13)$$

where

$$\frac{\partial W}{\partial g_1} = \frac{1}{g_1+\exp(W(g_1))} = \ell_1 \quad (14)$$

$$\frac{\partial g_1}{\partial I_{ph}} = \frac{R_s^2R_p^2I_0\exp(h_1)}{a^2V_t^2(R_s+R_p)^2} \quad (15)$$

Similarly, $\frac{\partial f_2}{\partial I_{ph}}$ can be achieved as:

$$\frac{\partial f_2}{\partial I_{ph}} = R_p - aV_t \times \frac{\partial W}{\partial g_2} \times \frac{\partial g_2}{\partial I_{ph}} \tag{16}$$

where

$$\frac{\partial W}{\partial g_2} = \frac{1}{g_2 + \exp(W(g_2))} = \ell_2 \tag{17}$$

$$\frac{\partial g_2}{\partial I_{ph}} = \frac{R_p^2 I_0 \exp(h_2)}{a^2 V_t^2} \tag{18}$$

Substitution of (13)-(18) in (12) results in:

$$\Delta P = \frac{\partial P}{\partial I_{ph}} \Delta I_{ph} = \left(I \frac{\partial f_2}{\partial I_{ph}} + V \frac{\partial f_1}{\partial I_{ph}}\right) \Delta I_{ph} = \left(V\left(\frac{R_p}{R_s+R_p} - \frac{\ell_1 R_s R_p^2 I_0 \exp(h_1)}{aV_t (R_s+R_p)^2}\right)\right) \Delta I_{ph} + \left(I\left(R_p - \frac{\ell_2 R_p^2 I_0 \exp(h_2)}{aV_t}\right)\right) \Delta I_{ph}. \tag{19}$$

Remark 2: It can be observed from (19) that $\frac{\partial (I=f_1)}{\partial I_{ph}} = \frac{R_p}{R_s+R_p} - \frac{\ell_1 R_s R_p^2 I_0 \exp(h_1)}{aV_t(R_s+R_p)^2} \neq 1$. The equality to one is only achieved for an ideal solar cell with $R_s \to 0$ and $R_p \to \infty$.

Through similar analysis, the impact of uncertainty in other four parameters is derived as follows:

$$\Delta P = \frac{\partial P}{\partial I_0} \Delta I_0 = \left(I \frac{\partial V}{\partial I_0} + V \frac{\partial I}{\partial I_0}\right) \Delta I_0 = \left(V\left(\frac{R_p}{R_s+R_p} - \frac{\ell_1 R_p \exp(h_1)}{(R_s+R_p)}\left(1 + \frac{R_s R_p I_0}{aV_t(R_s+R_p)}\right)\right)\right) \Delta I_0 + \left(I\left(R_p - \ell_2 R_p \exp(h_2)[1 + I_0 R_p]\right)\right) \Delta I_0. \tag{20}$$

$$\Delta P = \frac{\partial P}{\partial a} \Delta a = \left(I \frac{\partial V}{\partial a} + V \frac{\partial I}{\partial a}\right) \Delta a = \left(V\left(-\frac{W(g_1)V_t}{R_s} + \frac{\ell_1 I_0 R_p \exp(h_1)}{a(R_s+R_p)}\left(1 + \frac{R_p(R_s I_{ph} + R_s I_0 + V)}{aV_t(R_s+R_p)}\right)\right)\right) \Delta a + \left(I\left(-W(g_2)V_t + \frac{R_p I_0 \ell_2 \exp(h_2)}{a}\left[1 + \frac{R_p(I_{ph} + I_0 - I)}{aV_t}\right]\right)\right) \Delta a. \tag{21}$$

$$\Delta P = \frac{\partial P}{\partial R_s} \Delta R_s = \left(I \frac{\partial V}{\partial R_s} + V \frac{\partial I}{\partial R_s}\right) \Delta R_s = \left(V\left(\frac{V - R_p(I_0 + I_{ph})}{(R_s+R_p)^2} + \frac{W(g_1)aV_t}{R_s^2} - \frac{\ell_1}{R_s}\left(\frac{R_p^2 I_0 \exp(h_1)\left[1 + \frac{R_s(R_p I_{ph} + R_p I_0 - V)}{aV_t(R_s+R_p)}\right]}{(R_s+R_p)^2}\right)\right)\right) \Delta R_s + (I[-I]) \Delta R_s. \tag{22}$$

$$\Delta P = \frac{\partial P}{\partial R_p} \Delta R_p = \left(I \frac{\partial V}{\partial R_p} + V \frac{\partial I}{\partial R_p}\right) \Delta R_p = \left(V\left(\frac{V + R_s(I_0 + I_{ph})}{(R_s+R_p)^2} - \frac{\ell_1 R_s I_0 \exp(h_1)}{(R_s+R_p)^2}\left(1 + \frac{R_p(R_s I_{ph} + R_s I_0 + V)}{aV_t(R_s+R_p)}\right)\right)\right) \Delta R_p + \left(I\left(I_{ph} + I_0 - I - \ell_2 I_0 \exp(h_2)\left[1 + \frac{R_p(I_{ph} + I_0 - I)}{aV_t}\right]\right)\right) \Delta R_p. \tag{23}$$

The partial derivatives of power with respect to the unknown parameters can be considered as indices for local SA. Determining the impact of each parameter on the solar cell model using relations (19)–(23) is almost impossible due to the high nonlinearity and complexity of these equations. In other words, providing physical and analytical interpretations is impracticable because of the inherent complexity of these mathematical relations. Furthermore, the partial derivatives are highly dependent on the operating point of the solar cell, i.e., the point on the I–V characteristic. Therefore, the investigation of SA is carried out only numerically and is restricted to a few specific assumptions, as specified in the following.

3.1 Local Analysis

Here, without loss of generality, the R.T.C. France solar cell is selected to study the impact of parameter errors on the PV model. The datasheet values for this commercial solar cell at a temperature of $T = 33$ °C and solar irradiance of $G = 1000$ W/m^2 are provided in Table 1.

In another referenced study (Diab et al., 2020b), the Coyote Optimization Algorithm (COA) was utilized to estimate the unknown parameters of the R.T.C. France solar cell with the SDM. COA is reported to exhibit effective tracking performance, providing a good balance between the exploration and exploitation phases during global optimization. Additionally, the proposed algorithm was found to be highly precise and stable compared with other similar optimization algorithms. Simulations and practical validations demonstrate the superiority of COA for PV parameter estimation across different circuit models and diverse PV technologies under various operating conditions. The estimated parameters of the R.T.C. France solar cell with the SDM obtained using COA are reported in Table 2. Star (*) variables in this table represent the nominal values obtained from the COA algorithm. To perform local SA and assess the impact of parameter errors on output power performance, the estimated parameters in Table 2 are considered as nominal (baseline) values. Moreover, among all possible operating points on the I–V curve (from the short-circuit condition $(V, I) = (0, I_{sc})$ to open-circuit condition $(V, I) = (V_{oc}, 0)$), the MPP condition ($(V, I) = (V_{mp}, I_{mp})$) is considered. This is because the MPP condition is the most important operating point due to its maximum energy extraction from the PV cell (Ishrat et al., 2024). Additionally, condition monitoring of PV systems is typically based on measurements near the MPP (Lappalainen et al., 2024). Hence, we focus on operating the PV cell at its MPP, making SA at this point a reliable investigation. Although the partial derivatives represent local sensitivity indices, the power variation (ΔP) resulting from deviations in each parameter from its nominal value is also an important quantity to study. Therefore, the partial derivatives and the absolute power variation due to a 10% error in each parameter from its nominal value at the MPP condition are reported in Table 3. In other words, a 10% deviation from the baseline values in Table 2 is considered for each parameter, while the remaining parameters are kept constant. It should be noted that the variable θ in Table 3 refers to the five unknown electrical parameters (inputs) in the SDM representation. Moreover, the power–voltage (P–V) characteristics for the nominal parameters and for a 10% variation in each parameter around the MPP are shown in Figure 2. There is a very strong correspondence between the P–V curves in Figure 2 and the $|\Delta P|$ values in Table 3. It can be observed from Table 3 that I_0 has the highest absolute sensitivity value. However, the power variation for a 10% error in this parameter is almost ten times smaller than that of I_{ph}, because I_0 has a value on the order of 0–1 μA, while I_{ph} has a value between 0–1 A. This fact indicates that the scale of the parameter value is as important as its sensitivity. Although R_s has the absolute sensitivity value at 0.95, its power variation is second lowest. According to Table 3, I_{ph} has the third-highest sensitivity value, which is almost twice that of a. However, the absolute power variations for both I_{ph} and a are equal. The parallel resistance R_p has the minimum sensitivity, which also results in a very small power variation. There are also several other important points to consider, as stated in the following remarks.

Table 1. Datasheet parameters for R.T.C. France solar cell.

Characteristic	Symbol (unit)	Value
Open-circuit voltage	V_{oc} (V)	0.5728
Short-circuit current	I_{sc} (A)	0.7603
Voltage at maximum power	V_{mp} (V)	0.4507
Current at maximum power	I_{mp} (A)	0.6894
Maximum power	P_{mp} (W)	0.3107

Table 2. Estimated parameters for SDM of R.T.C. France solar cell by COA (Diab et al., 2020b).

Parameters	I_{ph}^* (A)	I_0^* (μA)	a^*	R_s^* (Ω)	R_p^* (Ω)
Values	0.76077	0.3084	1.47655	0.03655	52.82666

Table 3. Local derivative-based sensitivity analysis in the MPP condition.

Electrical parameters ($\boldsymbol{\theta}$)	**Partial derivative $\left(\frac{\partial P}{\partial \theta}\right)$**	$\boldsymbol{\lvert\Delta P\rvert}$
I_{ph}	0.85	0.065
I_0	-1.72×10^{5}	0.005
a	0.44	0.065
R_s	-0.95	0.004
R_p	1.5×10^{-4}	7.7×10^{-4}

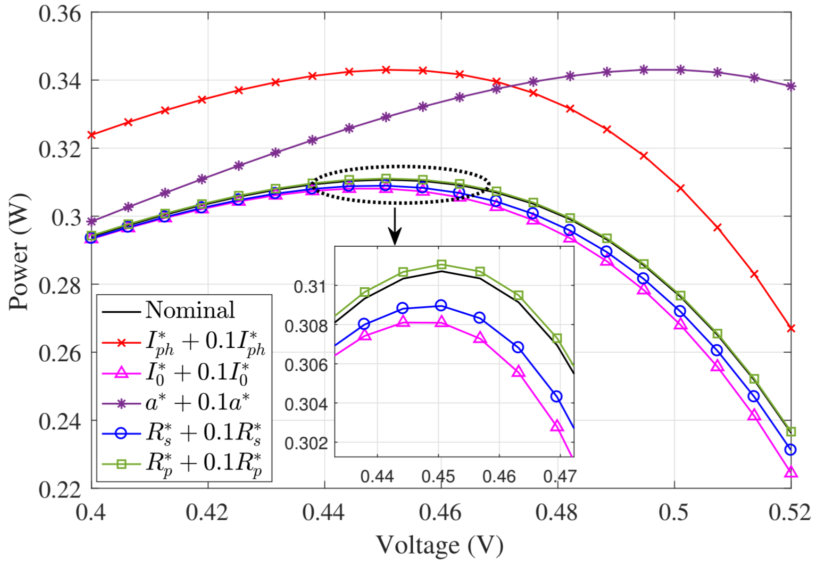

Figure 2. $\boldsymbol{P - V}$ curves of R.T.C. France solar cell at MPP for nominal parameters and their 10% error.

Remark 3: The 10% error in I_{ph} is highly unlikely, because this parameter typically has a value around I_{sc}. On the other hand, the diode ideality factor aaa can take any value between 1 and 2. Hence, considering $|\Delta P|$, the diode ideality factor can be regarded as the most influential parameter for SDM-based power generation in practice.

Remark 4: The aforementioned analysis has been applied to a PV cell. According to (4), for a PV module, the series resistance is given by $\bar{R}_s = N_s R_s$, where typically $N_s \geq 36$ for commercial modules. Therefore, in a PV module, $\bar{R}_s$ has higher impact than I_0 or even I_{ph}, considering the output performance of the SDM.

Remark 5: A similar discussion of the previous remark can be considered for the parallel resistance $\bar{R}_p = N_s R_p$ in a PV module. However, due to very low sensitivity of R_p, this parameter has minimum impact on the $P - V$ curve, even for a PV module.

3.2 Global Analysis

Although local analysis provides insight into the importance of the five unknown parameters, its reliability is limited. Firstly, the values reported in Table 2 may not be exact. Estimating the parameters of the SDM involves solving a highly non-convex optimization problem. Hence, more precise results may be obtained using different approaches, which motivates the widespread use of stochastic and metaheuristic algorithms. Secondly, even assuming that the reported values in Table 2 are accurate, the preceding analysis only captures the local behavior of the five parameters. A more robust approach would consider a feasible range of variation for each parameter rather than a single value. Furthermore, discrepancies have been observed between parameter prioritization based on partial derivatives and actual power variations, due to the significantly different magnitudes of the parameters, ranging from microamperes for I_0 to several hundred ohms for R_p. Therefore, a precise sensitivity analysis necessitates converting all inputs to dimensionless variables (Chirino and Xu, 2024). Here, a global SA based on partial derivatives (Sobol and Kucherenko, 2009) is applied to the SDM with five unknown parameters at the MPP. This approach requires less computation time than other global SA techniques, making it suitable for complex models. First, all variables should be normalized, i.e., the range of variation for each parameter is limited to 0–1. The MPP values of voltage and current are considered due to the significance of this point on the I–V curve. To achieve a normalized variable for the photocurrent (I'_{ph}), min–max normalization is applied as follows:

$$I'_{ph} = \frac{I_{ph}-I_{ph,min}}{I_{ph,max}-I_{ph,min}} \quad (24)$$

where $I_{ph,min}$ and $I_{ph,max}$ are the minimum and maximum feasible values for I_{ph}. The normalized variables I'_0, a', R'_s, R'_p can be achieved, similarly. The minimum and maximum values for each electrical parameter are stated in Table 4. Star ($*$) variables in this table are nominal values, which can be achieved using any metahuristic optimization algorithms.

Remark 6: Other normalization methods, including Z-score and decimal scaling, also exist. However, the commonly used min–max normalization technique is chosen due to its advantages over other methods. Firstly, it preserves the relative order and ratios between the original data points. Secondly, this method is suitable for our purpose and easy to apply, since *a priori* knowledge of the feasible bounds of the parameters is available.

For the R.T.C. France solar cell, the nominal values are stated in Table 2. Moreover, Δ represents variation in nominal values. For photocurrent I_{ph}, additional coefficients namely α and β are introduced to ensure that $I_{sc} \le I_{ph} \le 1.2I_{sc}$.

Table 4. Minimum and maximum values for electrical parameters in the SDM.

Electrical parameters	Minimum	Maximum
I_{ph}	$I^*_{ph} - \alpha\Delta I^*_{ph}$	$I^*_{ph} + \beta\Delta I^*_{ph}$
I_0	$I^*_0 - \Delta I^*_0$	$I^*_0 + \Delta I^*_0$
a	$a^* - \Delta a^*$	$a^* + \Delta a^*$
R_s	$R^*_s - \Delta R^*_s$	$R^*_s + \Delta R^*_s$
R_p	$R^*_p - \Delta R^*_p$	$R^*_p + \Delta R^*_p$

To have a comprehensive evaluation of global SA, $\Delta = 0.1$ and $\Delta = 0.3$ with $\alpha = 0.002$ and $\beta = 0.5$ are considered for R.T.C. France solar cell. By considering $\Delta = 0.3$ and the nominal values in Table 2, the following lower and upper bounds of inputs will be achieved:

$$\begin{cases} I_{sc} \le I_{ph}(A) \le 1.15I_{sc} \\ 0.21 \le I_0(\mu A) \le 0.4 \\ 1.03 \le a \le 1.92 \\ 0.025 \le R_s(\Omega) \le 0.0475 \\ 36.98 \le R_p(\Omega) \le 68.67 \end{cases} \quad (25)$$

Remark 7: The variation of $\Delta = 0.3$ considers a larger set in the neighborhood of the nominal values. However, this variation still ensures that all five parameters remain within their admissible ranges. The justification that the above inequalities are feasible can be supported by combinations of empirical data, datasheets of the considered SDM, and literature standards (Laudani et al., 2014; Jordehi, 2016; Moshksar and Ghanbari, 2017).

Now, all the normalized variables can be obtained using the min–max normalization method. Consequently, all normalized parameters have comparable weight within the range of 0 to 1.

Substituting the normalized variables into (8) and (9) and recalculating the output P at the MPP results in:

$$P = f(I'_{ph}, I'_0, a', R'_s, R'_p) = f_1(V) \times f_2(I)|_{(V,I)=(V_{mp},I_{mp})} \quad (26)$$

where function $f(I'_{ph}, I'_0, a', R'_s, R'_p)$ is defined in the unit hypercube H^5. Without loss of generality, it is assumed that the five normalized variables are independent random variables with values between 0 and 1. As indicated, the partial derivatives can only show the local sensitivity of P with respect to the normalized variables at specific points $I^*_{ph}, I^*_0, a^*, R^*_s, R^*_p$. However, it has been shown in Sobol and Kucherenko (2009) that a functional consisting of the integration over the corresponding hypercube of the squared partial derivative can be considered as an index for global SA. Here, the functionals are defined as:

$$\begin{cases} \nu_{I_{ph}} = \int_{H^5} \left(\frac{\partial f}{\partial I'_{ph}}\right)^2 dx' \\ \nu_{I_0} = \int_{H^5} \left(\frac{\partial f}{\partial I'_0}\right)^2 dx' \\ \nu_a = \int_{H^5} \left(\frac{\partial f}{\partial a'}\right)^2 dx' \\ \nu_{R_s} = \int_{H^5} \left(\frac{\partial f}{\partial R'_s}\right)^2 dx' \\ \nu_{R_p} = \int_{H^5} \left(\frac{\partial f}{\partial R'_p}\right)^2 dx' \end{cases} \quad (27)$$

where $dx' = dI'_{ph}dI'_0da'dR'_sdR'_p$ is Lebesque measure. Sobol and Kucherenko (2009) proved that there is a link between the ith functional (ν_i) and its global sensitivity index (S^T_i), as evident below:

$$S^T_i \le \frac{\nu_i}{\pi^2 D} \quad (28)$$

where D is the total variance of $P = f(I'_{ph}, I'_0, a', R'_s, R'_p)$. In fact, the proportional relation between ν_i and S^T_i in (28) reveals that variables with smaller values of ν have lower impact on the PV model performance in their admissible range of variations, and vice versa. Therefore, it is only required to obtain the partial derivatives with respect to the normalized variables analytically and then, calculate the five different quintuple integrals in (27), numerically. Since the partial derivatives are complex functions, numerical calculations of the functionals in (27) are time-consuming and require high-speed computing processors with parallel processing capabilities. Thus, the direct utilization of (27) in its current form is impractical. To address this problem, the functions $\frac{\partial f}{\partial I'_{ph}}, \cdots, \frac{\partial f}{\partial R'_p}$ are replaced with multivariable quadratic functions. For example, $\frac{\partial f}{\partial I'_{ph}}$ can be approximated as:

$$\frac{\partial f}{\partial I'_{ph}} \approx \sum_{i=1}^{5}\sum_{j=1}^{5} a_{ij}x_ix_j + \sum_{i=1}^{5} a_ix_i + a_0 \quad (29)$$

where $[x_1, x_2, x_3, x_4, x_5] = [I'_{ph}, I'_0, a', R'_s, R'_p]$. The unknown constant coefficients a_{ij}, a_i, and a_0 for $i, j = 1, \cdots, 5$ are estimated by least square technique. For this purpose, 100000 data are extracted uniformly from $\frac{\partial f}{\partial I'_{ph}}$ in H^5 hypercube space. Likewise, all the other four partial differential equations ($\frac{\partial f}{\partial I'_0}, \cdots, \frac{\partial f}{\partial R'_p}$) can be approximated by quadratic functions. Through the substitution of (29) in (27), the numerical values for the global sensitivity index at MPP can be simply achieved with very low computation cost and acceptable accuracy.

The coefficient of determination (R^2) is calculated for each approximated multivariable quadratic function to validate it with respect to the corresponding real function. R^2 values for approximated partial differential equations and the corresponding global index values (ν) are reported in Table 5 for R.T.C. France solar cell with SDM. Moreover, two parameters ranges of $\Delta = 0.1$ and $\Delta = 0.3$ are considered for accurate and comprehensive SA results.

Table 5. R^2 and ν values for each electrical parameter in R.T.C. France solar cell with $\Delta = 0.1$ and $\Delta = 0.3$.

Electrical parameters	R^2 ($\Delta = 0.1$)	ν ($\Delta = 0.1$)	R^2 ($\Delta = 0.3$)	ν ($\Delta = 0.3$)
I_{ph}	0.9995	5.5408×10^{-4}	0.9934	0.0054
I_0	0.9977	1.5325×10^{-4}	0.9664	0.0052
a	0.9959	0.0266	0.9745	1.7223
R_s	0.9995	6.3509×10^{-5}	0.9597	0.0024
R_p	0.9997	2.0344×10^{-6}	0.9863	1.8272×10^{-5}

For both $\Delta = 0.1$ and $\Delta = 0.3$, $R^2 > 0.95$ was achieved, indicating an acceptable and precise approximation of the partial derivative functions. Thus, the numerically calculated values for ν are reliable and provide a reasonable representation of global sensitivity.

Considering $\Delta = 0.1$, the diode ideality factor a has by far the highest sensitivity index. Following that, I_{ph} has the second-highest sensitivity value, which is approximately 3.6 times larger than that of I_0. For a solar cell, R_s has a global sensitivity value smaller than I_0. Finally, R_p has the lowest sensitivity index and, consequently, the least importance among all five SDM inputs. It should be noted that for a PV module, the series resistance R_s might be more important than I_0 and even I_{ph}. In the case of greater uncertainty for the estimated parameters, i.e., $\Delta = 0.3$, a similar sensitivity ranking is achieved. However, in this case, a becomes more dominant between other four parameters. Also, the sensitivity index value for I_{ph} is slightly larger than I_0. The main reason is that I_{ph} has a lower degree of uncertainty as it is expected to be close to I_{sc}. The difference between R_s and I_0 decreases for $\Delta = 0.3$, implying that more attention should be devoted to R_s estimation in black-box identification. Ultimately, the sensitivity index of R_p decreases for higher degrees of uncertainty in the electrical inputs of the SDM.

As a final interpretation, for parameter estimation of a single solar cell with the SDM using any metaheuristic algorithm, I_{ph} should be constrained between $(I_{sc}\ ,\ 1.1I_{sc}]$. Following that, the highest weight should be assigned to the diode ideality factor. For black box modeling, I_{ph} and I_0 should be estimated with similar weight and accuracy, but less than a. Then, R_s should be assigned less weight relative to I_{ph} and I_0. If the identification is applied to a commercial PV module, it is preferable to estimate R_s w with higher accuracy than both I_{ph} and I_0, but still less than the ideality factor. Finally, the parallel resistance R_p should have the lowest weight among all five parameters for a PV cell or module.

Remark 8: It should be noted that all the results from both local and global analyses are valid only at the MPP condition. At off-MPP conditions, entirely different results may be obtained. On the other hand, the MPP is by far the most important operating point on the I–V characteristic. Hence, it is logical to choose this point as the primary index among all other possible operating conditions. Moreover, the analyses and the corresponding results presented here are not valid under partial shading conditions, because the SDM is not a reasonable representation of the corresponding I–V curve under such conditions. Accordingly, the results are only justifiable under uniform solar irradiance.

Remark 9: The results of this study can be generalized to any PV cell technology for which an SDM provides an acceptable representation. If the SDM models the corresponding PV cell with a reasonable degree of accuracy, then the approaches and analyses of this study are valid. Fortunately, many PV cells can be modeled using an SDM with desirable accuracy.

Remark 10: The results of this SA investigation can be utilized in other real PV system applications, such as accurate SDM extraction, system monitoring, and the development of reliable fault detection algorithms. For single-diode modeling and parameter estimation, suitable weights for each parameter can be assigned according to the results of this study in the corresponding stochastic algorithm.

This will result in a more reliable SDM among the infinitely possible models, due to the non-convexity of the identification problem. For example, to obtain an SDM for a cell, it is logical to assign the largest weight to the diode ideality factor, while the lowest weight should be assigned to the parallel resistance. For PV system monitoring and/or fault detection, changes in parameter values or the rate of their change can be used as monitoring and/or detection indices. For instance, early aging, partial shading, hotspot conditions, and other mismatch conditions can be detected by real-time estimation of the SDM parameters. For this purpose, it is rational to focus on the most sensitive parameters, such as the diode ideality factor or, in large-scale PV systems, even the series resistance.

4. CONCLUSIONS

A PV cell with an SDM consists of five unknown electrical parameters: I_{ph}, I_0, a, R_s, and R_p. Determining the dominant parameters and their impact on PV output power can improve identification methods, model-based fault detection algorithms, and system monitoring. In this research, derivative-based local and global sensitivity analyses have been proposed to rank the five inputs according to their impact on the output.

Due to the importance of the MPP, all analyses and numerical calculations are performed at this operating condition. The numerical results from the global analysis reveal that the diode ideality factor, with a global index $\nu = 1.7223$ is by far the most dominant parameter in SDM performance. Considering the logical and feasible range $I_{sc} \le I_{ph} \le 1.15I_{sc}$, I_{ph} and I_0 hahave nearly equal global index values of $\nu \approx 0.0054$. Then, R_s is ranked as the fourth most influential parameter for P–V generation by the SDM, with a global index of $\nu = 0.0024$. Ultimately, R_p has the least impact on SDM performance at the MPP, with an index value of $\nu = 1.83 \times 10^{-5}$, showing a considerable difference from R_s. In the case of a PV module with N_s solar cells, R_s has a higher weight than I_0 and even I_{ph}, but still less than a. Since the index value of R_p is very low, it has the least importance in SDM performance under any circumstances.

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NOMENCLATURE

K	Boltzmann's constant (J/K)
q	Electron charge (C)
G	Irradiance (W/m^2)
T	Temperature (Kelvin)
I_{ph}	Photocurrent (A)
I_0	Diode saturation current (μA)
a	Diode ideality factor
R_s	Series resistance (Ω)
R_p	Parallel resistance (Ω)
I	Output current (A)
V	Output voltage (V)
P	Output power (W)
Greek letters	
θ	Five electrical parameters
ν	Functional
Δ	Varaiation from nominla value
α	Constant Coefficient
β	Constant Coefficient
Subscripts	
M	Module
A	Array

REFERENCES

1. Abdelminaam, D. S., Said, M., & Houssein, E. H. (2021). Turbulent flow of water-based optimization using new objective function for parameter extraction of six photovoltaic models, *IEEE Access*, *9*, 35382-35398. https://doi.org/10.1109/ACCESS.2021.3061529

2. Ahmed, M. T., Gonçalves,T., Albino, A., Rashel, M. R., Veiga, A., & Tlemcani, M. (2016). Different parameters variation analysis of a PV cell, *Proceedings of International Conference for Students on Applied Engineering (ICSAE)*, Newcastle Upon Tyne, UK, 1-5. https://doi.org/10.1109/ICSAE.2016.7810183

3. Arandian, B., Eslami, M., Kkalid, S., Khan, B. Sheikh, U. U., Akbari, E., & Mohammed, A. H. (2022). An effective optimization algorithm for parameters identifcation of photovoltaic models. *IEEE Access*, *10*, 34069-34084. https://doi.org/10.1109/ACCESS.2022.3161467

4. Bai, J., Liu, S., Hao, Y., Zhang, Z., Jiang, M., & Zhang, Y. (2014). Development of a new compound method to extract the fve parameters of pv modules, *Energy Conversion and Management, 79,* 294-303. https://doi.org/10.1016/j.enconman.2013.12.041

5. Bastidas-Rodriguez, J. D., Franco, E., Petrone, G., Ramos-Paja, C. A., & Spagnuolo, (2017a). G. Quantifcation of photovoltaic module degradation using model based indicators, *Mathematics and Computers in Simulation*, *131*, 101-113. https://doi.org/10.1016/j.matcom.2015.04.003

6. Bastidas-Rodriguez, J. D., Petrone, G., Ramos-Paja, C. A., & Spagnuolo, G. (2017b). A genetic algorithm for identifying the single diode model parameters of a photovoltaic panel, *Mathematics and Computers in Simulation*, *131*, 38-54. https://doi.org/10.1016/j.matcom.2015.10.008

7. Bharadwaj, P., Chaudhury, K. N., & John, V. (2016). Parameter identifcation for PV modules basedon an environment-dependent double-diode model, *IEEE Journal of Photovoltaics, 6,* 1261-1268. https://doi.org/10.1109/JPHOTOV.2019.2923336

8. Borgonovo, E., & Plischke, E. (2016). Sensitivity analysis: A review of recent advances, *European Journal of Operational Research*, *248*, 869-887. https://doi.org/10.1016/j.ejor.2015.06.032

9. Calasan, M., Aleem, S. H. E. A., & Zobaa, A. F. (2021). A new approach for parameters estimation of double and triple diode models of photovoltaic cells based on iterative Lambert W function, *Solar Energy*, *218*, 392-412. https://doi.org/10.1016/j.solener.2021.02.038

10. Chirino, H., & Xu, B. (2019). Parametric Study and Sensitivity Analysis of Latent Heat Thermal Energy Storage System in Concentrated Solar Power Plants, *ASME Journal of Solar Energy Engineering*, *141*(2), 021006. https://doi.org/10.1115/1.4042060

11. Chouder, A., Silvestre, S., Sadaoui, N., & Rahmani, L. (2012). Modeling and simulation of a grid connected PV system based on the evaluation of main PV module parameters, *Simulation Modelling Practice and Theory, 20,* 46-58. https://doi.org/10.1016/j.simpat.2011.08.011

12. Deb, S., Li, D., Sinha, S., Malik, P., Raina, G., & Wang, J. (2023). Local Energy System: A Comprehensive Review of Modelling, Tools and Pilot Projects, *Proceedings of International Conference on Power Electronics and Energy (ICPEE)*, Bhubaneswar, India. https://doi.org/10.1109/ICPEE54198.2023.10060751

13. Diab, A. A. Z., Sultan, H. M., Aljendy, R., Al-Sumaiti, A. S., Shoyama, M., & Ali, Z. M. (2020a). Tree growth based optimization algorithm for parameter extraction of different models of photovoltaic cells and modules, *IEEE Access*, *8*, 119668-119687. https://doi.org/10.1109/ACCESS.2020.3005236

14. Diab, A. A. Z., Sultan, H. M., Do, T. D., Kamel, O. M., & Mossa, M. A. (2020b). Coyote optimization algorithm for parameters estimation of various models of solar cells and PV modules, *IEEE Access*, *8*, 111102-111140. https://doi.org/10.1109/ACCESS.2020.3000770

15. ElShatter, T. F., & Elhagry, M. T. (1999). Sensitivity analysis of the photovoltaic model parameters, *Proceedings of 42nd Midwest Symposium on Circuits and Systems*, Las Cruces, USA, 1-4. https://doi.org/10.1109/MWSCAS.1999.867783

16. Et-torabi, K., Nassar-eddine, I., Obbadi, A., Errami, Y., Rmaily, R., Sahnoun, S., Fajri, A. E., & Agunaou, M. (2017). Parameters estimation of the single and double diode photovoltaic models using a Gauss–Seidel algorithm and analytical method: A comparative study, *Energy Conversion and Management*, *148*, 1041-1054. https://doi.org/10.1016/j.enconman.2017.06.064

17. Hao, Q., Zhou, Z., Wei, Z., & Chen, G. (2020). Parameters identifcation of photovoltaic models using a multi-strategy success-history-based adaptive differential evolution, *IEEE Access, 8,* 35979-35994. https://doi.org/10.1109/ACCESS.2020.2975078

18. Ishrat, Z., Gupta, A. K., & Nayak, S. (2024). Optimizing photovoltaic arrays: A novel approach to maximize power output in varied shading patterns, *Journal of Renewable Energy and Environment*, *11*(2), 75-88. https://doi.org/10.30501/jree.2023.415011.1674

19. Jain, A., & Kapoor, A. (2004). Exact analytical solutions of the parameters of real solar cells using Lambert W-function*, Solar Energy Materials & Solar Cells*, *81*, 269-277. https://doi.org/10.1016/j.solmat.2003.11.018

20. Jordehi, A. R. (2016). Parameter estimation of solar photovoltaic (PV) cells: A review, *Renewable and Sustainable Energy Reviews*, *61*, 354-371. https://doi.org/10.1016/j.rser.2016.03.049

21. Jumabekova, A., Berger, J., & Foucquier, A. (2021). An efcient sensitivity analysis for energy performance of building envelope: A continuous derivative based approach, *Building Simulation*, *14*, 909-930. https://doi.org/10.1007/s12273-020-0712-4

22. Khalid, C., Mohammed, F., & Mohcine, M. (2021). An accurate modelling of photovoltaic modules based on two-diode model, *Renewable Energy*, *167*, 294-305. https://doi.org/10.1016/j.renene.2020.11.085

23. Khezzar, R., Zereg, M., & Khezzar, A. (2014). Modeling improvement of the four parameter model for photovoltaic modules, *Solar Energy, 110,* 452-462. https://doi.org/10.1016/j.solener.2014.09.039

24. Khodapanah, M., Ghanbari, T., Moshksar, E., & Hosseini, Z. (2023). Partial shading detection and hotspot prediction in photovoltaic systems based on numerical differentiation and integration of the P-V curves, *IET Renewable Power Generation*, *17*(2), 279-295. https://doi.org/10.1049/rpg2.12596

25. Lappalainen, K., Piliougine, M., Valkealahti, S., & Spagnuolo, G. (2024). Photovoltaic module series resistance identifcation at its maximum power production, *Mathematics and Computers in Simulation*, *224*, 50-62. https://doi.org/10.1016/j.matcom.2023.05.021

26. Laudani, A., Fulginei, F. R., & Salvini, A. (2014). High performing extraction procedure for the one-diode model of a photovoltaic panel from experimental I-V curves by using reduced forms, *Solar Energy, 103,* 316-326. https://doi.org/10.1016/j.solener.2014.02.014

27. Li, S., Gong, W., & Gu, Q. (2021). A comprehensive survey on meta-heuristic algorithms for parameter extraction of photovoltaic models, *Renewable and Sustainable Energy Reviews*, *141*, 110828. https://doi.org/10.1016/j.rser.2021.110828

28. Malik, P., Awasthi, M., & Sinha, S. (2019). Analysis of sensitive parameters influencing a SPV/WT/Biomass/Battery based hybrid system, *Proceedings of 8th International Conference on Power Systems (ICPS)*, Jaipur, India. https://doi.org/10.1109/ICPS48983.2019.9067637

29. Mathew, D., Rani, C., Kumar, M. R., Wang, Y., Binns, R., & Busawon, K. (2018). Wind-driven optimization technique for estimation of solar photovoltaic parameters, *IEEE Journal of Photovoltaics, 8,* 248-256. https://doi.org/10.1109/JPHOTOV.2017.2769000

30. Meng, Z., Zhao, Y., Tang, S., & Sun,Y. (2020). An efcient datasheet-based parameters extractionmethod for two-diode photovoltaic cell and cells model, *Renewable Energy*, *153*, 1174-1182. https://doi.org/10.1016/j.renene.2020.02.084

31. Moshksar, E., & Ghanbari, T. (2017). Adaptive estimation approach for parameter identifcation of photovoltaic modules, *IEEE Journal of Photovoltaics*, *7*, 614-623. https://doi.org/10.1109/JPHOTOV.2016.2633815

32. Nazer, A., Manganiello, P., & Isabella, O. (2024). A virtual bus parallel differential power processing confguration for photovoltaic applications, *Mathematics and Computers in Simulation*, *224*, 49-62. https://doi.org/10.1016/j.matcom.2023.06.001

33. Ndi, F. E., Perabi, S. N., Ndjakomo, S. E., Abessolo, G. O., & Mengata, G. M. (2021). Estimation of single-diode and two diode solar cell parameters by equilibrium optimizer method, *Energy Reports, 7,* 4761-4768. https://doi.org/10.1016/j.egyr.2021.07.025

34. Oliva, D., Aziz, M. A. E., Elsheikh, A. H., & Ewees, A. A. (2019). A review on meta-heuristics methods for estimating parameters of solar cells, *Journal of Power Sources, 435,* 126683. https://doi.org/10.1016/j.jpowsour.2019.05.089

35. Ridha, H. M., Hizam, H., Mirjalili, S., Othman, M. L., Ya'acob, M. E., & Ahmadipour, M. (2022). Parameter extraction of single, double, and three diodes photovoltaic model based on guaranteed convergence arithmetic optimization algorithm and modifed third order Newton Raphson methods, *Renewable and Sustainable Energy Reviews*, *162*. https://doi.org/10.1016/j.rser.2022.112436

36. Shaheen, A. M., Ginidi, A. R., El-Sehiemy, R. A., & Ghoneim, S. S. M. (2021). A forensic-based investigation algorithm for parameter extraction of solar cell models, *IEEE Access*, *9*, 1-20. https://doi.org/10.1109/ACCESS.2020.3046536

37. Sobol, I. M., & Kucherenko, S. (2009). Derivative based global sensitivity measures and their link with global sensitivity indices, *Mathematics and Computers in Simulation*, *79*, 3009-3017. https://doi.org/10.1016/j.matcom.2009.01.023

38. Subhadarsini, A., Panda, B., & Nayak, B. (2022). Maiden application and control parameter sensitivity analysis of fractional order tilt integral derivative controller in standalone solar photovoltaic system, *Journal of Renewable Energy and Environment*, *9*, 85-100. https://doi.org/10.30501/jree.2022.312874.1274

39. Tian, H., Mancilla-David, F., Ellis, K., Muljadi, E., & P. (2012). A cell-to-module-to-array detailed model for photovoltaic panels, *Solar Energy*, *86*, 2695-2706. https://doi.org/10.1016/j.solener.2012.06.004

40. Tifdat, K., Maouhoub, N., Benahmida, A., & Salah, F. E. A. (2022). An accurate approach for modeling I-V characteristics of photovoltaic generators based on the two-diode model, *Energy Conversion and Management: X*, *14*, 100205. https://doi.org/10.1016/j.ecmx.2022.100205

41. Toledo, F. J., Galiano, V., Blanes, J. M., Herranz, V., & Batzelis, E. (2024). Photovoltaic single-diode model parametrization. An application to the calculus of the Euclidean distance to an I-V curve, *Mathematics and Computers in Simulation*, *225*, 794-819. https://doi.org/10.1016/j.matcom.2023.01.005

42. Wen, X., Abbes, D., & Francois, B. (2021). Modeling of photovoltaic power uncertainties for impact analysis on generation scheduling and cost of an urban micro grid, *Mathematics and Computers in Simulation*, *183*, 116-128. https://doi.org/10.1016/j.matcom.2020.02.023

43. Xu, J. (2022). Separable nonlinear least squares search of parameter values in photovoltaic models, *IEEE Journal of Photovoltaics, 12*, 372-379. https://doi.org/10.1109/JPHOTOV.2021.3126105

44. Xu, Y., Jin, W., & Zhu, X. (2017). Parameter identifcation of photovoltaic cell based on improved recursive least square method, *Proceedings of 20th International Conference on Electrical Machines and Systems (ICEMS)*, Sydney, Australia, 1-5. https://doi.org/10.1109/ICEMS.2017.8055947

45. Zhu, X. G., Fu, Z. H., Long, X. M., & Li, X. (2011). Sensitivity analysis and more accurate solution of photovoltaic solar cell parameters, *Solar Energy*, *85*, 393-403. https://doi.org/10.1016/j.solener.2010.10.022